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A Survey on Volatility Fluctuations in the Decentralized Cryptocurrency Financial Assets

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Abstract: This study is an integrated survey of GARCH methodologies applications on 67 empirical papers that focus on cryptocurrencies. More sophisticated GARCH models are found to better explain the fluctuations in the volatility of cryptocurrencies. The main characteristics and the optimal approaches for modeling returns and volatility of cryptocurrencies are under scrutiny. Moreover, emphasis is placed on interconnectedness and hedging and/or diversifying abilities, measurement of profit-making and risk, efficiency and herding behavior. This leads to fruitful results and sheds light on a broad spectrum of aspects. In-depth analysis is provided of the speculative character of digital currencies and the possibility of improvement of the risk–return trade-off in investors' portfolios. Overall, it is found that the inclusion of Bitcoin in portfolios with conventional assets could significantly improve the risk–return trade-off of investors' decisions. Results on whether Bitcoin resembles gold are split. The same is true about whether Bitcoins volatility presents larger reactions to positive or negative shocks. Cryptocurrency markets are found not to be efficient. This study provides a roadmap for researchers and investors as well as authorities.

Keywords: decentralized cryptocurrency; Bitcoin; survey; volatility modelling

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1. Introduction

The continuing evolution of cryptocurrency markets and exchanges during the last few years has aroused sparkling interest amid academic researchers, monetary policymakers, regulators, investors and the financial press. The skyrocketing increase in cryptocurrency market values during 2017 has generated particular attention on the returns and volatility of these highly speculative digital assets. This has brought to the forefront a heated debate about whether the volatility of Bitcoin and other cryptocurrencies can be estimated with accuracy. An avenue of particular interest when studying the volatility of cryptocurrencies is the specification of the appropriate methodology in order for the volatility pattern to be investigated. GARCH modeling casts light on interconnectedness among financial assets, hedging and/or diversifying capabilities, (in) efficiency in markets, profit opportunities and risk of losses, as well as herding phenomena.

Böhme et al. (2015) support that the advantage of Bitcoin in comparison with former cryptographic cash lies in its decentralized core technologies. These prohibit large concentration of power into a single person or organization. They notice though that the decentralization of Bitcoin is not yet fruitful due to concentration among a small number of intermediaries in the Bitcoin ecosystem. Selgin (2015) expresses the belief that Bitcoin engenders the interesting probability that a synthetic commodity money can be created. This could be based on a production protocol that should work as well as a monetary rule. This type of money would be eligible to serve for fighting inflationary loss of value. Yermack (2015) argues that Bitcoin has no characteristics that are superior to traditional currencies and that it has been created for speculation purposes rather than for transactions.

Hendrickson et al. (2016) support the idea that that even if a government bans Bitcoin a significant portion of economic agents would remain willing to accept it for payments. Additionally, they claim that preference for Bitcoin should be higher in economies enjoying elevated technological levels or suffering from hyperinflation in their national currencies. Baur et al. (2018a) document that Bitcoin is not like traditional financial assets either in normal or stressed periods. They argue that Bitcoin is digital money within a decentralized peer-to-peer payment network. It is believed to constitute a hybrid between fiat currency and commodity currency. No intrinsic value exists in Bitcoin and no government or monetary authority affects its function. Moreover, in accordance with Yermack (2015), they support that Bitcoin is mainly employed for speculation rather than as a means of payments or transactions. On the contrary, Ammous (2018) claims that Bitcoin can serve as a store of value due to its low supply growth, its protocol design and the lack of a regulatory authority. Nevertheless, other large-cap cryptocurrencies cannot.

This paper contributes to academic literature on cryptocurrencies by casting light on one of the most important aspects in their behavior, which is volatility dynamics. This integrated survey adds to Corbet et al. (2019b) that constitutes the only complete and multi-spectral literature review about digital currencies up to the present. Moreover, surveys and empirical studies have been conducted on various Bitcoin characteristics such as bubbles in market values (Cheah and Fry 2015; Kyriazis et al. 2020), spillovers to other markets (Kyriazis 2019b), efficiency and profitable trading (Kyriazis 2019a; Fang et al. 2020), the connection between Bitcoin and precious metals (Dyhrberg 2016a; Kyriazis 2020b, 2020c; Papadamou et al. 2021). Moreover, review and empirical papers investigate the behavioral aspects of cryptocurrencies (Gurdgiev and O'Loughlin 2020; Kyriazis 2020a; Papadamou et al. 2021), impacts of economic conditions (Wang et al. 2019; Kyriazis 2021a) or geopolitical influences on digital currencies (Aysan et al. 2019; Kyriazis 2021c). The present study follows the lines of Gries et al. (2018); Belke and Fahrholz (2018); Belke and Beretta (2020); Papadamou et al. (2020); and Kyriazis (2021b). The axes of our GARCH-based investigation have been the best model selection, the special features of cryptocurrencies as well as the presence or not of efficiency in these markets. Furthermore, prominence has been given to the analysis of interconnectedness and hedging or diversifying abilities, profitable opportunities and risk of losses as well as herding behavior in contrast to personal beliefs of investors.

It should be emphasized that risk and return are positively connected as regards asset pricing (Ghysels et al. 2005). This is the reason why a large bulk of research has been devoted to the examination of volatility in financial assets that permits investors with speculative motives to increase the profitability of their portfolios (Al-Yahyaee et al. 2019; Wellenreuther and Voelzke 2019). Generalized Autogressive Conditional Heteroscedasticity Models are suitable for estimating the fluctuations of investment assets that exhibit large levels of volatility (Chou 1988; Hansen and Lunde 2005). The large number of GARCH specifications enables the interested researcher to trace the appropriate model that better represents the patterns by which market values fluctuate. Thereby, this study enlightens even in the slightest degree and provides a better understanding of how the markets of these highly risky digital assets behave. This enriches the arsenal of financial decision-making by investors with all levels of risk-aversion and especially of those who defy risk.

The remainder of this study proceeds as follows. Section 2 presents the empirical outcomes and implications derived from academic work with GARCH specifications focusing on Bitcoin's volatility. Section 3 lays out GARCH empirical results concerning a wider spectrum of cryptocurrencies. At the latter part of this section, analysis of the economic implications of findings takes place. Finally, Section 4 presents the economic implications of findings and concludes. Table A1 in the Appendix A presents an overall view of the main characteristics of each paper.

2. Literature on Bitcoin

The literature on cryptocurrencies has rapidly emerged. Special emphasis has been attributed to the discovery of returns and volatility characteristics of Bitcoin as this constitutes the largest-cap and most famous digital currency. Furthermore, it is considered the most influential among virtual currencies and one of the most hopeful substitutes of gold and the US dollar. Academic research on Bitcoin has been largely based on GARCH methodologies and presents four main axes. Firstly, the selection of the optimal model, the examination of Bitcoin characteristics and important factors that influence this cryptocurrency are under scrutiny. Secondly, the hedging and/or diversifying linkages with traditional assets are investigated. Thirdly, the profit opportunities or dangers of losses are discussed. Finally, the efficiency dynamics in Bitcoin markers are under consideration.

2.1. Bitcoin Characteristics and Influencing Factors

Among the first empirical studies related to modelling returns and volatility of Bitcoin for investigating characteristics and influencing factors have been Glaser et al. (2014); Gronwald (2014) and Bouoiyour and Selmi (2015, 2016). More specifically, Glaser et al. (2014) explore the users' intentions when they hold domestic currency and exchange their money for digital currencies. The GARCH methodology is adopted. They support that the initial attention given to Bitcoin and the usage of Bitcoin in transactions have increased the demand for this cryptocurrency. The users' motives are primarily speculative. Gronwald (2014) investigates Bitcoin price movements by the use of GARCH and jump-intensity GARCH models. Estimations provide evidence that Bitcoin prices are characterized by extreme price fluctuations. Moreover, it is argued that jump-intensity GARCH more appropriate for estimations than the conventional GARCH methodology. This provides a sign that the Bitcoin market is not mature. Bouoiyour and Selmi (2015) use ARCH, GARCH, EGARCH, APARCH, weighted GARCH and GARCH CMT-GARCH specifications to examine Bitcoin volatility. There is evidence that Threshold GARCH (TGARCH) IS the optimal model for estimation during the period December 2010–June 2015 while the EGARCH methodology is the most suitable for the period from January 2015 to June 2015. During the first period, a long memory process and duration of persistence are detected in the Bitcoin market. Nevertheless, during the second period, the persistence of volatility is lower. The Bitcoin market is not found to be mature. Strong asymmetries remain and negative shocks are more likely to influence Bitcoin compared to positive shocks. In a similar mentality, Bouoiyour and Selmi (2016) employ ARCH, GARCH, EGARCH, APARCH, weighted GARCH and Component with Multiple Thresholds (CMT-GARCH) models for estimating Bitcoin price dynamics. The results indicate that the CMT-GARCH and APARCH specifications are more reliable. The evidence supports that Bitcoin has been less volatile since January 2015. It is revealed that bad news influences Bitcoin market values more than good news and that the Bitcoin market is not mature.

Papers that constitute the early literature on cryptocurrencies and have formed the basis for further research include Katsiampa (2017); Corbet et al. (2017); Blau (2018) and Aharon and Qadan (2018) and Conrad et al. (2018). Katsiampa (2017) performs Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Exponential GARCH (EGARCH), TGARCH, Asymmetric Power ARCH (APARCH), Component GARCH (CGARCH) and AC-GARCH estimations in order to find out which methodology provides the best fit to Bitcoin. The findings reveal that both a short-run and a long-run component of Bitcoin's conditional variance should be captured and this is the reason why the AR-CGARCH model is found to be preferable. Corbet et al. (2017) examine the impacts on Bitcoin of alterations in international monetary policy by adopting a GARCH methodology. The findings provide evidence that decisions about monetary policy based on interest rates taken by the US Federal Open Market Committee (FOMC) are significantly influential. Furthermore, it is found that quantitative easing announcements by the Federal Reserve, the Bank of England, the European Central Bank and the Bank of Japan increase Bitcoin volatility. Blau (2018) adopts GARCH models for examining Bitcoin price dynamics. Estimations reveal that speculative trading in Bitcoin markets is not to blame for Bitcoin's volatility. Moreover, it is not responsible for the abrupt fall in Bitcoin's market value. Moreover, Aharon and Qadan (2018) employ the OLS and GARCH models for the period 2010–2017 in order to examine whether the day-of-the-week effect exists in Bitcoin markets. The findings support that both returns and volatility of Bitcoin present the Monday effect as they appear to be higher on that day. They also reveal that Bitcoin is not affected by speculative factors from the capital, bond or commodity markets. Nevertheless, it has significant resemblances to traditional financial assets such as equities, bonds and currencies. By their own perspective, Conrad et al. (2018) perform estimations about long-term and short-term volatility components in digital currencies by using a GARCH-MIDAS methodology. They reveal that the SP500 realized volatility exerts a negative and significant impact on long-term Bitcoin volatility. On the contrary, the SP500 volatility risk premium and the Baltic dry index have a positive impact on long-term fluctuations of Bitcoin. Moreover, they argue that there is a strong linkage of Bitcoin volatility and global economic uncertainty. Finally, Charles and Darné (2019) provide a replication of Katsiampa (2017) by employing GARCH, EGARCH, Glosten-Jagannathan-Runkle-GARCH (GJR-GARCH), APARCH, CGARCH and Asymmetric Component GARCH (AC-GARCH) methodologies. They adopt the same as well as an extended sample. Estimations and robustness analysis provide evidence that none of the GARCH frameworks adopted is appropriate for modeling Bitcoin returns.

Later literature on special Bitcoin features and determinants investigated by GARCH-based specifications includes more advanced methods or focus their research on aspects not studied until then. Koutmos (2019) uses a Markov regime-switching model and documents that interest rates, implied stock market volatility and foreign exchange market volatility are asset pricing risk factors that influence Bitcoin returns. These returns are found to be less explicable when high fluctuations in Bitcoin markets appear. The market risk factors under scrutiny are revealed not to be equally good explanators of Bitcoin prices. Narayan et al. (2019) adopt GARCH methodologies in order to examine whether increases in Bitcoin prices influenced monetary aggregates in Indonesia during the 2010–2017 period. Based on the results, they argue that higher Bitcoin market values result in higher inflation, appreciation of the national currency and weakening of money velocity. This justifies the Bank of Indonesia taking action concerning Bitcoin trading. By another approach, Yu et al. (2019) adopt the GJR-GARCH methodology and extensions in order to conduct an analysis of the characteristics of volatility in Bitcoin prices and account for volatility asymmetry. Furthermore, they trace the mechanism by which the information volume affects price fluctuations. The outcomes indicate that the Bitcoin market does not present the volatility asymmetry that generally exists in financial markets and the market efficiency is characterized by more positive volatility asymmetry in relation to these markets. Moreover, volatility is found to be highly persistent. Furthermore, the results indicate that the Bitcoin market supports the sequential information arrival hypothesis and that day's trading volume, and Google Trends also significantly influences the volatility of returns. Furthermore, Troster et al. (2019) perform GAS and GARCH analysis for forecasting risk and returns of Bitcoin. More specifically, they compare out-of-sample 1% Value-at-Risk (VaR) forecasts under 45 different specifications, using three backtesting procedures. Empirical outcomes indicate that GAS models with heavy-tailed distribution are the most appropriate for Bitcoin modeling. Moreover, heavy-tailed GARCH or GAS models are found to be more efficient in estimations than GARCH models with normal distributions.

Moreover, Yu (2019) employ high-frequency data and the Model Confidence Set (MCS) test along with Homogeneous Autoregressive (HAR) and HARCH specifications in order to find out whether jump components and leverage effects are crucial for forecasting Bitcoin volatility. The evidence indicates that the leverage impact significantly affects future Bitcoin volatility, while jumps and the Economic Policy Uncertainty (EPU) index are not found to be influential. Moreover, it is supported that adding the leverage effect and the EPU index to the benchmark model can significantly improve the predictive ability of the latter.

When it comes to Jin et al. (2019), they investigate which of Bitcoin, gold and crude oil is most influential for price fluctuations in a system. This is the reason why they conduct multifractal detrended cross-correlation (MF-DCCA), multivariate GARCH (MVGARCH) and information share (IS) analyses. Based on the MF-DCCA results, Bitcoin is found to be the mostly influenced from price changes in gold and crude oil markets. Moreover, the GARCH-related outcomes indicate higher volatility spillovers towards the same direction. The IS estimations confirm that gold is the most influential asset compared to Bitcoin and crude oil and constitutes a major determinant of hedging powers in portfolios.

2.2. Bitcoin and Hedging and/or Diversifying Abilities

The existence of hedging or diversifying abilities of Bitcoin against conventional assets such as stocks, bonds, currencies or commodities have attracted a significant level of researchers' attention. Dyhrberg (2016a, 2016b); Bouri et al. (2017) and Baur et al. (2018b) have been the most influential papers at the beginning of this strand of literature. Dyhrberg (2016a) adopts a number of GARCH methodologies in order to compare Bitcoin characteristics with those of gold and the US dollar. The outcomes show that the Exponential GARCH is the most suitable model for estimations. It is found that Bitcoin, gold and the USD carry many similarities. Furthermore, Bitcoin reacts to the Federal Reserve rate (FFR), is symmetrically responsive to good and bad news and can act as a hedger. Overall, Bitcoin is somewhere between a pure store of value and a pure medium of exchange so is neither identical to gold nor to the US dollar. In a somewhat different mentality, Dyhrberg (2016b) uses TGARCH models to look into the hedging abilities of Bitcoin against conventional assets during the period from mid-2010 until mid-2015. Econometric outcomes provide evidence that Bitcoin can clearly act as a hedge against the FTSE index but its hedging influence is weaker against the US dollar and is mostly present in the short-run. Overall, it is argued that Bitcoin has resemblances with gold as it can be used for improving the risk–return trade-off in investors' portfolios. Bouri et al. (2017) adopt daily and weekly data and a DCC-GARCH framework for examining the hedging and safe haven properties of Bitcoin against major stock indices, bonds, gold, oil as well as the general commodity and the US dollar indices. Econometric outcomes reveal that Bitcoin is appropriate for diversification purposes but not for hedging. It is found that it constitutes a safe haven only against weekly extreme down movements against Asian stocks. Moreover, its hedging and safe haven abilities are not stable over time. Moreover, Baur et al. (2018b) replicate Dyhrberg (2016a) by using the same sample and methodologies as well as alternative models. Notably, they reach different outcomes compared to Dyhrberg (2016a). They provide evidence that Bitcoin is significantly different from gold and fiat money as it presents unique risk–return features and its volatility process is not similar to that of traditional assets. Furthermore, no correlation is detected with the latter.

Later researchers have employed a number of different and advanced GARCH methodologies in order to better capture interlinkages between Bitcoin and traditional assets. Al Janabi et al. (2019) perform liquidity-adjusted Value-at-Risk (LVaR) optimization based on vine copulas and LVaR models and GARCH, EGARCH, GJR-GARCH and APARCH specifications concerning Bitcoin, stock markets of the G7 countries, gold and commodities. Empirical outcomes provide evidence that Bitcoin and gold are useful in improving the risk–return trade-off of the G7 stock portfolio. It is also found that Bitcoin performs better only when long-positions are allowed while gold achieves better performance only in short-selling conditions. Moreover, Kang et al. (2019) perform DCC-GARCH estimations and wavelet coherence analysis for the examination of hedging and diversification capacities of gold futures in relation to Bitcoin market values. Based on econometric results, they argue for volatility persistence, causality and phase differences between the two variables. The European Debt Crisis (2010–2013) is found to increase contagion. Moreover, it is revealed that strong comovement takes place across the 8–16 weeks frequency band according to wavelet coherence outcomes. In a similar vein, Chan et al. (2019) employ daily, weekly and monthly data and GARCH, DCC-GARCH and CCC-GARCH models as well as the frequency dependence regression model for examining hedging abilities of Bitcoin against worldwide stock indices. Results by monthly data reveal that Bitcoin is a powerful hedger against all indices examined. Furthermore, medium-frequency data in frequency dependence tests lead to outcomes that reveal strong hedging abilities against the SP500 and the EUROSTOXX indices. Moreover, estimations with the same methodology but low-frequency data denote that Bitcoin is a very good hedger against the Shanghai A-share index.

Sophisticated and alternative GARCH methodologies are also employed by Klein et al. (2018); Symitsi and Chalvatzis (2018) and Guesmi et al. (2019). Klein et al. (2018) implement a BEKK-GARCH model for estimating the time-varying conditional correlations and compare the properties of conditional variance of Bitcoin and gold. They argue that Fractionally Integrated Asymmetric Power ARCH (FIAPARCH) is the best-fitting model and that Bitcoin has an asymmetric response to market shocks, which is in the same direction as that of precious metals. Nevertheless, gold and Bitcoin behave completely differently in markets, as the former is considered to be reliable during crises whereas the latter presents falls in prices in distressed times. It is found that Bitcoin carries no hedging abilities and does not resemble traditional assets. When it comes to Symitsi and Chalvatzis (2018), they employ the VAR(1)- BEKK- GARCH and the DCC-GARCH methodologies to look into spillover impacts between Bitcoin and energy and technology companies. Econometric results indicate the existence of return spillovers from the latter to the former. Moreover, volatility spillovers from technology firms to Bitcoin are detected while Bitcoin exerts long-run volatility impacts on stocks of fossil fuel and clean energy companies. Overall, shock spillovers between Bitcoin and equity indices are bidirectional and present a negative sign. It should be noted that low correlations between them could prove beneficial for portfolio managers. Urquhart and Zhang (2019) use hourly data and the GARCH, EGARCH, GJR-GARCH, DCC-GARCH and ADCC-GARCH frameworks for examining the hedging or safe haven abilities of Bitcoin against major national currencies. The results reveal that Bitcoin can act as a hedge at an intraday level against the CHF, EUR and GBP while acting as a diversifier against the AUD, CAD and JPY. Furthermore, estimations by the Hansen (2000) test indicate that Bitcoin constitutes a safe haven against the CAD, CHF and GBP during extremely distressed periods. As concerns Guesmi et al. (2019), they employ different multivariate GARCH methodologies in order to examine conditional cross-impacts and volatility spillovers between Bitcoin and financial indicators. Outcomes provide evidence that the VARMA(1,1)-DCC-GJR-GARCH model is the most appropriate for estimations of joint dynamics of Bitcoin and other financial assets. It is argued that hedging strategies involving Bitcoin, gold, oil and stock markets in emerging countries improve the risk–return nexus in a portfolio more than if Bitcoin was not included. Overall, Bitcoin is found to be a significant diversifier and hedger and a short position in Bitcoin allows hedging against all assets under scrutiny. Moreover, Kristoufek (2021) employs the Generalized VAR methodology based on Diebold and Yilmaz (2014) and directed spillovers based on the forecast error variance decomposition for estimating whether stablecoins influence other cryptocurrencies. The results display that no such impacts exist. Nevertheless, when the number of stablecoin issuances becomes higher, the demand for crytpocurrencies is found to increase.

2.3. Bitcoin and Profit-Making or Losses

Profit-making opportunities in Bitcoin markets have been the subject of Akcora et al. (2018) and Ardia et al. (2019). To be more precise, Akcora et al. (2018) employ blockchain graphs and subgraphs (chainlets) as well as GARCH modeling to predict influences on Bitcoin price and volatility. Estimations reveal that the inclusion of extreme chainlet activities as external regressors in the variance equation leads to a significant amelioration in the GARCH specification for the prediction of extreme losses concerning the next day. Additionally, Ardia et al. (2019) test whether regime changes exist in the GARCH volatility dynamics of Bitcoin. They employ Markov-switching (MS-GARCH) methodologies. Furthermore, they conduct comparisons of MS-GARCH to traditional GARCH specifications for predicting VaR one-day ahead. Empirical evidence detects that regime changes exist in the GARCH process. MS-GARCH is found to be superior to conventional single-regime models for predictions of the VaR.

2.4. Bitcoin and Efficiency

Among the mostly important matters for Bitcoin investors has been the speed by which relevant news become priced-in as regards Bitcoin markets. Three academic studies have centered interest in examining such efficiency dynamics in these markets. Firstly, Vidal-Tomás and Ibañez (2018) explore by an AR-CGARCH-M model whether semi-strong efficiency exists concerning Bitcoin in the Bitstamp and Mt. Gox markets in response to Bitcoin-related events and monetary policy events. The findings indicate that shocks in Bitcoin markets have been priced-in in a faster pace as time passes. They argue that the Bitcoin market has taken steps towards higher levels of efficiency after the bankruptcy of Mt. Gox. Nevertheless, there is no evidence that monetary policy news influence Bitcoin's market values. Furthermore, Aggarwal (2019) employs ARCH, GARCH, EGARCH and TGARCH methodologies in order to investigate whether market inefficiency and random walk behavior are valid in Bitcoin markets. Strong evidence of market inefficiency is provided and absence of a random walk model is detected. It is supported that asymmetric volatility clustering is to be held responsible for delays in pricing-in as regards markets. Besides, Sensoy (2019) employs permutation entropy with GARCH(1,1) filtered returns and a rolling window approach in order to test for weak-form efficiency of Bitcoin prices with high-frequency data. Bitcoin values are taken in respect to EUR and USD. Empirical outcomes reveal that the BTC/USD and BTC/EUR have been rendered more informationally efficient since early 2016 and that the former is slightly more efficient than the latter. It should be noted that estimations with higher-frequency data provide evidence for lower efficiency. Moreover, higher liquidity in Bitcoin markets is beneficial for informational efficiency whereas the opposite holds for the volatility–efficiency nexus.

3. Literature on a Spectrum of Cryptocurrencies

Most of the recent academic research has dedicated a lot of effort to identifying and measuring interconnectedness among cryptocurrencies. This type of research has become significantly more frequent since the appearance of bull markets during 2017. The increasing popularity of digital currencies as investment assets has drawn attention towards diversifying and hedging strategies in portfolios consisting of cryptocurrencies alone or with conventional assets. There have been four main research strands in multiple digital currencies' examination. First, there is a significant amount of academic papers focusing on best model selection and the characteristics of virtual currencies. Moreover, the very important subjects of correlations, hedging or diversifying abilities and volatility spillovers across cryptocurrencies are investigated. Thirdly, results related to the profit, Value-at-Risk and Expected Shortfall measures that are especially interesting for investors are analyzed. Finally, yet importantly, the existence of herding phenomena owing to irrational behavior is under scrutiny.

3.1. Best Model Selection and Characteristics

The selection of the best GARCH methodology for modelling returns and volatility in digital currencies has been among the major concerns of researchers that focus on a range of such currencies. A number of alternative specifications have formed the methodology of empirical papers in order to find the best-fit model for each cryptocurrency. Chu et al. (2017) adopt twelve GARCH models in order to investigate the behavior of Bitcoin, Dash, Dogecoin, Litecoin, Maidsafecoin, Monero and Ripple. Econometric estimations reveal that the Integrated GARCH (IGARCH) and the GJR-GARCH methodologies provide the best fits in terms of modeling volatility in the majority of the digital currencies under scrutiny. Furthermore, Cheikh et al. (2020) use a number of GARCH models, including the smooth-transition GARCH (ST-GARCH) specifications for detecting whether asymmetric volatility dynamics exist in Bitcoin, Ethereum, Ripple and Litecoin. The reason for selecting this methodology is for capturing intermediate states for two extreme volatility regimes. The results indicate that an inverted asymmetric reaction takes place in most cryptocurrencies. This means that good news is more influential on volatility than bad news. Furthermore, the positive linkage between returns and volatility reveals the possibility of digital currencies to act as safe-havens. Moreover, Fakhfekh and Jeribi (2019) employ GARCH, EGARCH, TARCH, PGARCH, Fractionally Integrated GARCH (FIGARCH) and Fractionally Integrated Exponential GARCH (FIEGARCH) methodologies with different error distributions for selecting the optimum model concerning sixteen digital currencies. Econometric results provide evidence that TGARCH with double exponential distribution is the best model for modeling the majority of the cryptocurrencies examined. Asymmetric effects are detected and volatility is found to increase more when positive than negative shocks take place. This differs from what happens in stock markets. In the same mentality of employing innovative GARCH models is the study of Mensi et al. (2019). They adopt GARCH, FIGARCH, FIAPARCH and Hyperbolic GARCH (HYGARCH) specifications and investigate how structural breaks influence the dual long-memory levels of Bitcoin and Ethereum. Their findings reveal that market efficiency and the random walk hypothesis are not valid in the markets of Bitcoin and Ethereum and that Bitcoin presents different regimes. Long-memory characteristics and shifts are detected both in the mean and variance but they decrease significantly after accounting for structural breaks. It is argued that the FIGARCH model with structural breaks is a superior forecasting methodology for the cryptocurrencies examined.

Peng et al. (2018); Catania et al. (2018) and Omane-Adjepong et al. (2019) adopt GARCH specifications but also alternative methodologies for estimations. Peng et al. (2018) employ daily and hourly data on Bitcoin, Ethereum and Dash as well as the EUR, GBP and JPY. Moreover, they adopt GARCH methodologies with machine learning approaches for estimating volatility and look into mean and volatility equations using Support Vector Regression (SVR). Furthermore, the Diebold–Mariano test and Hansen's Model Confidence Set (MCS) have been employed. The results indicate that the SVR-GARCH specification outperforms GARCH, EGARCH and GJR-GARCH models with alternative distributions when forecasting volatility. Moreover, Catania et al. (2018) account for long memory and asymmetric reaction to past values and predict the conditional volatility of Bitcoin, Ethereum, Ripple and Litecoin. They employ a GARCH methodology and the Score-Driven-GHSKT model with: (i) leverage, (ii) time-varying skewness and (iii) fractional integration in the volatility process. The results reveal that more sophisticated volatility models that include leverage and time-varying skewness can provide more accurate volatility predictions at different forecast horizons from 1% to 6%. In a somewhat different vein, Omane-Adjepong et al. (2019) employ ARFIMA-FIGARCH models under two different distributions and a modified log-periodogram method in order to investigate inefficiency and persistence. The markets of the eight largest-cap cryptocurrencies are under scrutiny. They find that inefficiency and persistence are highly influenced by time-scales, the measure of returns and volatilities and regime shift. Overall, it is supported that lack of efficiency characterizes the markets of Bitcoin, Ethereum, Ripple, Litecoin, Monero, Stellar, Dash and NEM.

3.2. Correlations, Hedging or Diversifying Abilities and Volatility Spillovers

Volatility spillovers are a topic of major importance in financial markets. There has been a focus on markets of the most important financial assets, such as in Shahzad et al. (2021) that investigated US stock markets. They estimate quantile return spillovers among US equity sectors during the COVID-19 outbreak. The quantile factor VAR and the generalized forecast error variance decomposition (GFEVD) methodologies are adopted. The evidence supports that the overall US sectoral spillovers increase substantially during extreme events and non-ordinary market conditions. Furthermore, a mildly increasing trend is detected regarding connectedness in the bulk while there is a decreasing one in the tails, so a slow convergence is revealed.

Particular attention is paid to interlinkages, hedging or diversifying nexus and spillovers among digital currencies. Corbet et al. (2020) by the use of GARCH methodology investigate the connection of digital assets to alterations in US monetary policy. The latter is expressed by the US interest rate or by taking quantitative easing action. It is found that protocol-based assets display a significantly different reaction than currency-based applications. Mineable digital assets are significantly more influenced by monetary policy volatility spillovers and feedback than non-mineable. Currencies present an increase whereas Protocols a decrease and Decentralized Applications are not affected by global systematic liquidity spillovers. Not all assets are comparable to Bitcoin. Additionally, Corbet et al. (2019a) employ GARCH and DCC-GARCH models for investigating the KODAKCoin behavior before and after the first announcement of KODAKCoin on 9 January 2018. Furthermore, its nexus with Bitcoin and stock markets is under scrutiny. Estimations provide evidence of higher share prices and price volatility of the Kodak firm after the news about the KODAKCoin launch. This gives credence to the existence of a new form of asymmetric information. Moreover, a higher correlation is detected between the value of Kodak stock and Bitcoin.

Cahn et al. (2019) employ the cumulative sum test for parameter stability, the Granger causality test, the LM test for ARCH and the DCC-MGARCH methodology to analyze structural breaks and volatility spillovers in Bitcoin, Litecoin, Ripple, Stellar, Monero, Dash and Bytecoin. Econometrics estimations present that structural breaks exist in all the cryptocurrencies examined. It should be emphasized that shifts spread from small-cap digital currencies towards larger-cap ones. Moreover, volatility spillovers are also detected. The existence of strong positive correlations indicates no diversification possibilities among digital currencies. In a similar line of thought is the study of Kyriazis et al. (2019). They use a large number of alternative ARCH and GARCH specifications in order to look into which model is more suitable for estimating the nexus between each of twelve large-cap cryptocurrencies and Bitcoin, Ethereum and Ripple during distressed times. Evidence indicates that Exponential, Threshold and Asymmetric Power specifications can better envisage the behavior of the majority of the digital currencies investigated. Overall, no hedging abilities are detected among high-cap virtual currencies. By employing a somewhat similar perspective, Akyildirim et al. (2020) use high-frequency data to examine the linkage between price volatility of a wide spectrum of digital currencies and the implied volatility in the US and European financial markets. They employ GARCH and DCC-GARCH methodologies. The results show that there is time-varying positive connectedness between the conditional correlations of digital currencies and stress in financial markets. Especially, strong volatility is detected in cryptocurrences during the highest deciles of implied volatility in stock markets. That means that higher fluctuations exist during high investor fear in markets, as expressed by the VIX and VSTOXX indices.

In a similar mentality, Baur and Dimpfl (2018a) adopt the TGARCH methodology and the QAR-based asymmetric volatility estimator for examining asymmetric volatility in the 20 highest-cap digital currencies. Their findings reveal that volatility increases by a larger extent because of positive shocks in relation to negative ones. Furthermore, it is found that uninformed investors in a lower degree than markets of the other cryptocurrencies examined dominate Bitcoin and Ethereum markets. Furthermore, Aslanidis et al. (2019)

employ a DCC-GARCH methodology in order to investigate conditional correlations between large-cap cryptocurrencies, equity and bond indices and gold. They provide evidence that correlations are not stable over time (they range between 0.16 and 0.31) and have a positive sign. It is found that correlations with the Monero digital currency fluctuate less than the other. Furthermore, it is revealed that virtual currencies and traditional financial assets do not present strong nexus between them. Bouri et al. (2020) study the linkage between cryptocurrencies and the downside risk in equity investments by employing a DCC-GARCH methodology. Their evidence reveals that digital currencies can serve as hedgers and diversifiers against stock indices, especially those in the Asia–Pacific region and Japan, but such abilities are not constant over time. Furthermore, portfolio analysis confirms the benefits of using virtual currencies as hedgers. Omane-Adjepong and Alagidede (2019) employ wavelet-based methodologies, GARCH and GJR-GARCH specifications and parametric and non-parametric tests to trace the direction of volatility spillovers across markets of Bitcoin, Ripple, Litecoin, Stellar, Monero, Dash and BitShares. They support that probable diversification benefits exist pairwise and as a whole. Moreover, the trading scales and the proxy for market volatility are important determinants of the level of connectedness and volatility of causal linkages.

Not surprisingly, there is also a strand of recent empirical papers that employ more advanced GARCH forms. More specifically, Katsiampa (2019a, 2019b); Katsiampa et al. (2019a, 2019b); Beneki et al. (2019); Charfeddine et al. (2019); Tiwari et al. (2019) and Tu and Xue (2018) use diagonal BEKK-GARCH and/or asymmetric DCC-GARCH specifications.

Katsiampa (2019a) employs a bivariate Diagonal BEKK model in order to examine the volatility dynamics of Bitcoin and Ethereum. It is found that interdependencies exist between them and that their conditional volatility is time-varying and is influenced by very important news. Furthermore, it is revealed that Ethereum can act as a hedge against Bitcoin. Notably, analysis based on optimal portfolio weights leads to evidence that Bitcoin should outweigh Ethereum. Furthermore, Katsiampa (2019b) adopts an asymmetric diagonal BEKK model for the examination of volatility dynamics in cryptocurrencies of major importance. Findings indicate that conditional variances of each digital currency examined are influenced by previous squared errors and past conditional volatility. Moreover, asymmetric past shocks are found to affect the current conditional covariance (with Stellar Lumen being the exception). Examination of the covariances brings about similar results. Moreover, conditional correlations have a positive sign and vary with time. It can be noted that the most important news trigger volatility reactions and that each of Bitcoin and Litecoin present one structural breakpoint in the conditional variance.

In the same vein, Katsiampa et al. (2019a) employ hourly data for Bitcoin, Ethereum, Litecoin, Dash, Ethereum Classic, Monero, NEO and OmiseGO and investigate conditional volatilities and volatility co-movements by Diagonal BEKK and Asymmetric Diagonal BEKK methodologies. Evidence indicates that conditional variances are receivers of significant impacts by previous squared errors and past conditional volatility. It is found that investors pay more attention to news about NEO while they pay the least attention to information about Dash. Furthermore, shocks in Bitcoin are found to be the most persistent whereas shocks in OmiseGO are the least persistent ones. Moreover, the findings about conditional covariances are in accordance with the findings about conditional variances so strong linkages are traced among cryptocurrencies. It is supported that the Asymmetric Diagonal BEKK specification is the most suitable for the estimation of volatility characteristics. It should be noted that conditional correlations are not stable as time passes. Moreover, Katsiampa et al. (2019b) investigate conditional volatilities as well as conditional correlations between pairs of cryptocurrencies by employing three pairwise bivariate BEKK models. Estimations reveal that the conditional volatility of each digital currency depends on its own past shocks and volatility. A bidirectional shock transmission impact is detected in the Bitcoin-Ethereum and Bitcoin-Litecoin pairs. Furthermore, a unidirectional shock is traced from Ethereum to Litecoin. Moreover, the volatility spillover effects are bidirectional between all pairs. It is argued that conditional correlation is mostly positive but changes overtime.

Beneki et al. (2019) also employ a multivariate BEKK-GARCH methodology and impulse response VAR analysis for investigating volatility spillovers and hedging abilities between Bitcoin and Ethereum. Their results indicate the existence of significant swaps in the time-varying correlation. Furthermore, there is a delayed positive response of Bitcoin volatility on a positive volatility shock on Ethereum returns. It is argued that the diversifying capabilities of these digital currencies have existed but keep weakening after the bull period in cryptocurrency markets. This enables investors to take advantage of profitable opportunities in the inefficient Bitcoin market as shocks need time to be priced-in. Tu and Xue (2018) perform Granger causality tests and BEKK-GARCH estimations for investigating return and volatility spillovers between Bitcoin and Litecoin. Empirical outcomes reveal that such spillovers run only from Bitcoin to Litecoin before the bifurcation of Bitcoin and so the creation of Bitcoin Cash takes place on 1 August 2017. Notably, the direction of shock transmission is found to be reversed after that day. Overall, it is argued that Bitcoin's bifurcation has substantially weakened its role as the dominant and most influential currency in the markets of digital currencies.

Charfeddine et al. (2019) examine the dynamic linkage of cryptocurrencies with major financial securities and commodities by adopting different time-varying copula approaches and BEKK-GARCH, DCC-GARCH and ADCC-GARCH models. Econometric estimations provide evidence that there is no strong cross-correlation with traditional assets. This nexus is found to be weak and so indicates that digital currencies can serve as diversifiers in portfolios. Nevertheless, only weak hedging abilities are detected in the majority of correlations. It can be noted that external economic and financial shocks are influential for the linkages investigated. Not far from Charfeddine et al. (2019); Tiwari et al. (2019) employ the copula-ADCC-EGARCH methodology and rolling windows in order to examine the time-varying correlations between Bitcoin, Ethereum, Ripple, Litecoin, Dash and Stellar and the SP500 index. They argue that time-varying correlations are very low, particularly before 2017. Digital currencies can act as hedgers against the SP500 and Ethereum is the most effective among these hedgers. Furthermore, it is found that responses are stronger when negative shocks take place in the markets under scrutiny.

3.3. Profit, Value-at-Risk and Expected Shortfall

Studies on profit or losses due to trading on cryptocurrencies have not been numerous but are quite influential, such as Acereda et al. (2020); Boako et al. (2019) and Caporale and Zekokh (2019). More specifically, Acereda et al. (2020) employ GARCH, CGARCH, Non-linear GARCH (NGARCH) and TGARCH specifications and various error distributions for estimating the Expected Shortfall (ES) of Bitcoin, Ethereum, Ripple and Litecoin. Econometric outcomes provide evidence that the ES of Bitcoin should be estimated by adopting a non-normal error distribution with at least two parameters as well as the NGARCH or CGARCH models. It is found that heavy-tailed distributions produce better results than the normal distribution. Furthermore, Boako et al. (2019) use vine–copula approaches and GARCH expressions for modeling the codependence and Value-at-Risk in a portfolio with Bitcoin, Ethereum, Ripple, Litecoin, Dash and Stellar. Evidence reveals that strong interdependencies exist among digital currencies that are characterized by a dynamic dependency structure. Powerful dependencies are traced between Bitcoin and Ethereum. Furthermore, Litecoin, Ripple and Dash present a nexus with Bitcoin while Litecoin is the only one having directly dependence with it. Additionally, Ethereum constitutes the optimal choice in terms of risk–return if a no-shorting constraint is valid and investors select to use the efficient frontier. Moreover, Caporale and Zekokh (2019) look for the most suitable GARCH specification for modeling the volatility of Bitcoin, Ethereum, Ripple and Litecoin. They estimate a one-step ahead prediction of Value-at-Risk and Expected Shortfall by using rolling windows. Backtesting VaR and ES and the MCS test for loss functions then leads to selection of the best model. They argue that inclusion of asymmetries and regime switching such as happens with TGARCH and GJR-GARCH models can significantly improve predictions and so investment decisions.

3.4. Herding Phenomena

The herding phenomenon has been of primary concern among investors. GARCH models, along with alternative methodologies, have managed to cast light in some aspects of this irrational behavior. Ballis and Drakos (2019) use data on Bitcoin, Ethereum, Ripple, Litecoin, Dash and Monero and adopt cross-sectional deviation methods and a GARCH methodology to test for herding behavior in the cryptocurrency market. Based on their results, they argue that people act irrationally and imitate others in contrast to their beliefs, so herding exists. Their evidence reveals that when positive price movements take place, market dispersion follows market movements in a faster rhythm in comparison to negative movements. By their own perspective, Kumar and Anandarao (2019) explore the volatility spillover dynamics of Bitcoin, Ethereum, Ripple and Litecoin. They use of a IGARCH(1,1)-DCC(1,1) multivariate GARCH methodology and wavelet coherence analysis. They support that Bitcoin exerts significant volatility spillovers from Bitcoin to Ethereum and Litecoin. Such spillovers are found to have strengthened after 2017. Furthermore, moderate return comovements are presented among returns of cryptocurrencies. Pairwise wavelet cross-spectral analysis confirms these findings while wavelet coherence measures provide evidence for persistence of correlations in the short-run. These outcomes reveal herding behavior in digital currency markets.

King and Koutmos (2021) investigate whether herding and feedback trading behavior appears in the markets of nine major crytpocurrencies. Evidence reveals that heterogeneity exists in the types of feedback trading strategies employed across markets. Investors in Bitcoin, Ethereum, Ripple, and Cardano present trend chasing behaviour while investors in EOS and Stellar adopt contrarian trading. Overall, it is argued that herding exists in cryptocurrency markets and this phenomenon constitutes a determinant of the evolution of market values. Furthermore, Koutmos and Payne (2021) test an intertemporal regime-switching asset pricing model with heterogeneous agents that form different expectations concerning the patterns of Bitcoin price and volatility. By adopting the EGARCH methodology, among others, they support the notion that investors based on the fundamental value of cryptocurrencies (fundamentalists) prefer to trade when market values significantly deviate from fundamental values. Additionally evidence reveals the existence of speculators that employ ''band-wagon" behavior and purchase during bull markets while sell during bear markets. Notably, fundamentalists employ contrarian-type investing in conditions of low fluctuations in market values whereas behave more like fundamental traders when price uncertainty is high.

Moreover, Coskun et al. (2020) employ a number of alternative methods in order to investigate whether cryptocurrency markets exhibit herding behavior. They argue that anti-herding behavior emerges especially during periods with high volatility and that uncertainty was influential on this outcome. Nevertheless, no symmetric character in herding phenomena was detected when comparing upwards with downwards periods. From their viewpoint, Gurdgiev and O'Loughlin (2020) center their interest on how behavioral drivers via sentiment analysis influence herding phenomena appearances. More specifically, they investigate public sentiment impacts on investment markets and primarily on cryptocurrencies. The outcomes reveal that the direction of market values can be predicted by this index. These predictions could be enhanced by adopting natural language AI in order to better represent investor sentiment when expressing volatility, uncertainty, complexity and ambiguity factors.

4. Conclusions

This paper provides an integrated survey of empirical research on GARCH modeling and the relevant economic implications in cryptocurrency markets. Econometric estimations in the 67 primary studies under scrutiny shed light on the optimal methodologies for modeling returns and volatility of digital currencies. Furthermore, interlinkages and herding and/or diversifying capabilities between cryptocurrencies and traditional financial assets or among digital currencies are investigated. Moreover, outcomes concerning whether efficiency holds in cryptocurrency markets are presented. The analysis also covers profit-making opportunities, Value-at-Risk or Expected Shortfall measures related to trading in these markets. Additionally, the existence of herding behavior is examined. This broad spectrum of findings provides a roadmap for relevant multiperspective research and enables academics, traders, regulatory authorities and policymakers to benefit from an in-depth understanding of innovative payments and investment forms.

This survey builds on the significant yet still proliferating literature on cryptocurrency return and volatility dynamics, which have to be explained by Autoregressive Conditional Heteroskedasticity specifications. It is found that a large range of GARCH-based models have been used in relevant academic research. The GARCH, EGARCH, TGARCH, GJR-GARCH, APARCH, NGARCH, CGARCH, IGARCH, HARCH, ST-GARCH, MS-GARCH, HYGARCH and SVR-GARCH models are among the most popular ones. More complex volatility specifications, such as FIAPARCH, ARFIMA-FIGARCH, GARCH-MIDAS, BEKK-GARCH, VAR-BEKK-GARCH and copula-ADCC-EGARCH are also adopted. This indicates the existence of exponential, threshold, asymmetric, component, power, regime-switching, homogeneous autoregressive and even more complex behavior in the volatility of cryptocurrencies. It is found that more sophisticated GARCH methodologies better explain the sudden ups and downs in the market values of such forms of money and treat better the great difficulty inhibited in predicting their prices.

The economic implications of GARCH-type methodologies in academic papers about digital currencies are of great importance. Overall, it is found that the inclusion of Bitcoin in portfolios with conventional assets could significantly improve the risk–return trade-off of investors' decisions. Diversification abilities of Bitcoin are detected, which are usually not combined with hedging abilities. There is a significant bulk of literature supporting that Bitcoin is a hedger (especially against the US or Asian stock markets) but strong hedging abilities are not always traced. The evidence reveals that the SP500 significantly affects but is also influenced by Bitcoin and Ethereum but not in all cases examined. The results on whether Bitcoin resembles gold are split. The same goes for econometric outcomes that reveal whether Bitcoin volatility presents larger reactions to positive or negative shocks. Economic policy uncertainty, investor fear and monetary policy impacts are found to be influential towards digital currencies. Moreover, the evidence indicates that cryptocurrency markets are far from fully efficient. Nevertheless, they tend to better approach the efficient status as time passes and this tendency has started since the bull market in 2017.

When examining interrelations among cryptocurrencies, it is revealed that the largest capitalization and most liquid ones are found to be tightly interconnected. Somewhat surprisingly, not only large-cap currencies affect less popular ones but also the reverse impact takes place. Moreover, herding phenomena are found to exist across the markets of digital currencies. This tendency towards investing based on the opinion of the other market participants could be attributed to the very high level of uncertainty generated by the tremendous gap between the nominal and fundamental values in cryptocurrencies. Interestingly, the high level of non-linearities and asymmetries in price behavior can be expressed by a broad range of GARCH specifications considered as appropriate after checking for the best fit in each case. Thereby, behavior in cryptocurrencies cannot be rationally described or explained by conventional methods. This renders forecasting very difficult for investors but also leaves much space for profitable opportunities.

Due to the highly increasing popularity of digital currency investments and the largely bubbly character that they exhibit, cryptocurrencies prove capable of overcoming doubts regarding their utility as forms of liquidity and investments. It is hotly debated whether this skyrocketing form of price bubbles could continue being active for long in the future. The emergence of stablecoins and actions towards the creation and adoption of central bank digital currencies strengthens the viewpoint that cryptocurrencies are taking steps towards becoming widely accepted forms of payments and investments. Nevertheless, the rapid increases in market values remain largely inexplicable. Thereby, in the future emphasis is expected to be given to the investigation of herding behavior in the cryptocurrency markets and return and volatility clustering and convergence should probably attract much academic effort. Comovements and spillovers among cryptocurrencies or between them and alternative assets will also be receivers of increased interest by financial analysts. Apart from that, the bubble character of returns will probably become an even more important topic of investigation so GARCH-based or new advanced methodologies will help towards this direction of empirical research.

This survey provides a bird's eye view on the volatility dynamics of digital currencies and poses new challenges for academic researchers, policymakers, investors and the financial press. Potential avenues for future research on cryptocurrencies should include the thorough investigation of profit-making opportunities in combination with uncertainty in the global financial system and ways for improving the stability of digital assets. Moreover, the academic debate should focus on the regulatory implications of large levels of volatility in cryptocurrency markets. Research on stablecoins and central bank digital currencies should advance and provide feedback for comparison with decentralized cryptocurrencies. Fiscal and monetary authorities should indispensably take into consideration the consequences of private digital money as concerns the control of money supply and the efforts that authorities make to increase the welfare of citizens.

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Appendix A

Table A1. Overview of studies on GARCH modelling.

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Acereda et al. (2020)	FRL	Bitcoin Litecoin Ripple Ethereum	18 July 2010–31 July 2018	Daily	Coindesk.com	Generalized ARCH (GARCH) by Bollerslev (1986) Component GARCH (CGARCH) by Lee and Engle (1993) Non-linear GARCH (NGARCH) Threshold-GARCH (TGARCH) by Zakoian (1994) Rolling-window backtesting technique	An extension of GARCH and a non-normal error distribution with a t least two parameter are essential for estimating the Expected Shortfall
Aggarwal (2019)	RIE	Bitcoin	19 July 2010–20 March 2018	Daily	Coindesk.com	ARCH Generalized ARCH (GARCH)by Bollerslev (1986) Exponential GARCH (EGARCH) by Nelson (1991) Threshold ARCH (TARCH) by Glosten et al. (1993)	Strong market inefficiency and absence of random walk model due to asymmetric volatility clustering. Significant positive asymmetric volatility so positive news are more influential than negative news.
Aharon and Qadan (2018)	FRL	Bitcoin VIX Risk factor variable 'Bitcoin' and 'Bitcoin price' in Google trends (Google Search volume) Treasury Bill Weighted dollar exchange rate SP500 index	October 2010–October 2017	Daily	Bitcoincharts.com CBOE website Prof. French's Library Board of Governors of the Federal Reserve System (US)	OLS GARCH by Bollerslev (1986) Quasi-Maximum Likelihood estimation (QMLE) as in Bollerslev and Wooldridge (1992)	Mondays generate higher returns and volatility. Strong independence of Bitcoin from speculative factors.
Akcora et al. (2018)	EL	Bitcoin	1 January 2012–10 July 2017	Daily	Coinbase.com	Subgraphs (chainlets) ARMA(2,2)-GARCH(1,1) based on Bollerslev (1986) ARMA(2,2)-GARCHX(1,1)	The inclusion of extreme chainlet regressors in the variance equation in GARCH estimations results in better prediction of extreme next-day losses

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Akyildirim et al. (2020)	FRL	Bitcoin Cash (BCH) Bitcoin (BTC) Bitcoin Gold (BTG) Datum (DAT) DSH (Dashcoin) Eidoo (EDO) EOS Ethereum Classic (ETC) Ethereum (ETH) Metaverse ETP (ETP) IoT Chain (IOT) Litecoin (LTC) NEO Omise GO (OMG) QSH QTM Recovery Right Token (RRT) Santiment Network Token (SAN) Monero (XMR) Ripple (XRP) Yoyow (YYW) VIX (CBOE-traded) VSTOXX (DAX-traded)	22 June 2017–through midnight on the 24 June 2018	Data of 5-, 10-, 15-, 30-, and 60-min intervals	Bitfinex exchange Kaiko digital asset store	GARCH(1,1) by Bollerslev (1986) DCC-GARCH by Engle (2002)	Higher volatility when higher investor 'fear' in the US and Europe (higher positive nexus of conditional correlation between cryptocurrencies and financial market stress)
Al Janabi et al. (2019)	Phys	National stock market indices of: Canada, France, Germany, Italy, Japan, UK, US Gold Global commodity index Bitcoin	19 July 2010–31 January 2018	Daily	Thomson Datastream Coindesk.com	C-vine copula Liquidity Value-at-Risk (LVaR) optimization Markowitz mean-variance (MV) optimization Symmetric GARCH(1,1) by Bollerslev (1986) EGARCH(1,1) by Nelson (1991) GJR-GARCH(1,1) by Glosten et al. (1993) APARCH(1,1) by Ding et al. (1993)	C-vine LVar measure proves to be superior than Markowitz MV measure for VaR Bitcoin and gold improve the performance of the G7 stock portfolio Bitcoin performs better with long-positions whereas gold with short-selling

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Antonakakis et al. (2019)	JIFMIM	Bitcoin Ethereum Ripple Dash Litecoin Monero Nem Stellar BitShares	7 August 2015–31 May 2018	Daily	Coinmarketcap.com	TVP-FAVAR by Diebold and Yilmaz (2014) DCC-GARCH t- copula based on Engle (2002)	The higher is market uncertainty, the stronger is connectedness among cryptocurrencies Dynamic total connectedness presents large dynamic variability ranging from 25% to 75%. Bitcoin remains very important, but Ethereum becomes the top influencer
Ardia et al. (2018)	FRL	Bitcoin	18 August 2011–3 March 2018	Daily (midprices)	Datastream	GARCH(1,1) by Bollerslev (1986) EGARCH by Nelson (1991) GJR-GARCH by Glosten et al. (1993) MSGARCH as in Ardia et al. (2018)	Regime changes exist in the GARCH volatility dynamics of Bitcoin MSGARCH is a better predictor of VaR than conventional single-regime GARCH models
Aslanidis et al. (2019)	FRL	Bitcoin Dash Monero Ripple SP500 US Treasury bond 7-10 year index Gold bullion LBM	21 May 2014–27 September 2018	Daily	Coinmarketcap.com Eikon Thomson Reuters	DCC-GARCH by Engle (2002)	Cryptocurrencies present similar correlations among them, ranging from 0.16 to 0.31. Correlations with Monero are more stable over time Very weak correlations between cryptocurrencies and traditional financial assets
Ballis and Drakos (2019)	FRL	Bitcoin Dash Ethereum Litecoin Monero Ripple	August 2015–December 2018	Daily	Cryptocompare.com Coinmarketcap.com	Cross-sectional standard deviation (CSSD) by Christie and Huang (1995) Cross-sectional absolute deviation (CSAD) by Chang et al. (2000) GARCH(1,1) by Bollerslev (1986)	Investors act irrationally and imitate others with no reference to their own beliefs. The upevents market dispersion follows market movements more rapidly compared to the down events

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Baur and Dimpfl (2018b)	EL	Bitcoin Ethereum Ripple Litecoin Bitcoin Cash Monero Dash NEO EOS Stellar Cardano Tether IOTA TRON Ethereum Classic Binance Coin NEM Tezos Zcash OmiseGO	28 April 2013–8 August 2018 (Bitcoin, Ethereum) Since each one's introduction—8 August 2018 (for each of the rest cryptocurrencies)	Daily	Coinmarketcap.com	TGARCH by Zakoian (1994) Asymmetric response measure δ as in Baur and Dimpfl (2018a)	Larger increases of volatility due to positive shocks than negative shocks Weaker phenomenon of uninformed investors in markets of Bitcoin and Ethereum compared to other digital currencies
Baur et al. (2018b)	FRL	Bitcoin Gold Gold futures US dollar USD/GBP exchange rate USD/EUR exchange rate FTSE100 MSCI World	19 July 2010–22 May 2015	Daily	Coindesk.com Datastream	GARCH(1,1) E-GARCH(1,1) EGARCH(1,1)-X GJR-GARCH(1,1)-X	Bitcoin exhibits unique risk–return characteristic, follows a different volatility process and is uncorrelated with other assets (including gold and the US dollar) Replication by different GARCH specifications brings different results compared to Dyhrberg (2016a)

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Beneki et al. (2019)	RIBAF	Bitcoin Ethereum	8 August 2015–10 June 2018	Daily	Coinmarketcap.com	Diagonal Baba-Engle-Kraft-Kroner (BEKK)-GARCH(1,1) by Engle and Kroner (1995) Diagonal Vech-GARCH Diagonal BEKK-TGARCH	Bitcoin and Ethereum act as strong diversifiers only in bull markets. Significant swaps in time-varying correlations. Inefficiency in Bitcoin markets (delayed positive response of Bitcoin volatility on a positive volatility shock in Ethereum returns)
Blau (2018)	RIBAF	Bitcoin 51 other currencies (as benchmark)	17 July 2010–1 June 2014	Daily	Bitcoin Charts Bloomberg	GARCH(1,1) by Bollerslev (1986) GMM by Newey and West (1987)	Speculative trading does not contribute to Bitcoin's price falls neither to its high volatility
Boako et al. (2019)	IE	Bitcoin Dash Ethereum Litecoin Ripple Stellar	September 2015–June 2018	Daily	CryptoCompare.com	C-vine and R-vine copulas by Aas et al. (2009) AR(1)-GARCH(1,1) by Bollerslev (1986) Equally weighted portfolio construction	Strong dependencies among cryptocurrencies Ethereum provides the optimal risk–return trade-off subject to a no-shorting constraint for portfolio investors employing the efficient frontier
Bouoiyour and Selmi (2015)	MPRA	Bitcoin	December 2010–June 2015 January 2015–June 2015	Daily	Blockchain (https://blockchain.info/)	ARCH by Engle (1982) GARCH by Bollerslev (1986) EGARCH by Nelson (1991) APARCH by Ding et al. (1993) Weighted GARCH by Bauwens and Storti (2009) Component with multiple thresholds-GARCH (CMT-GARCH) by Bouoiyour and Selmi (2014)	TGARCH is the optimal model for the 1st period, while EGARCH is the best for the 2nd period examined Long memory process in 1st period Less volatility persistence for Bitcoin in 2nd period High levels of asymmetry Bitcoin is mainly driven by negative shocks

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Bouoiyour and Selmi (2016)	EB	Bitcoin Price Index	1 December 2010–22 July 2016	Daily	Blockchain (https://blockchain.info/)	ARCH by Engle (1982) GARCH by Bollerslev (1986) EGARCH by Nelson (1991) APARCH by Ding et al. (1993) Weighted GARCH by Bauwens and Storti (2009) Component with multiple thresholds-GARCH (CMT-GARCH) by Bouoiyour and Selmi (2014)	Although it maintains a moderate volatility, Bitcoin remains reactive to negative rather than positive news CMT-GARCH and APARCH are the optimal models for estimations
Bouri et al. (2020)	FRL	Bitcoin Ethereum Ripple Litecoin Stellar MSCI USA MSCI Europe MSCI Asia Pasific (excl. Japan) MSCI Japan	7 August 2015–31 July 2018	Daily	Coinmarketcap.com	DCC-GARCH by Engle (2002)	Bitcoin, Ethereum and Litecoin are hedgers and diversifiers especially against Asian Pacific and Japanese equities. Such abilities exhibit a time-varying character
Bouri et al. (2017)	FRL	Bitcoin (exchange rate of Bitcoin to US dollars from the BitStamp marketplace) by Brandvold et al. (2015) SP500 FTSE100 DAX30 NIKKEI225 Shanghai A-share Morgan Stanley Capital International (MSCI) World MSCI Europe MSCI Pacific Standard&Poor's Goldman Sachs (SPGS) commodity index Pimco Investment Grade Corporate Bond Index Exchange-Traded Fund (ETF)	18 July 2011–22 December 2015	Daily Weekly	Thomson Reuters Datastream	DCC-GARCH by Engle (2002)	Bitcoin is far more suitable for diversification than for hedging Serves as a powerful safe haven only against weekly extreme down movements in Asian stocks. Bitcoin's hedging and diversifying capabilities are time-varying

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Cahn et al. (2019)	FRL	Bitcoin Litecoin Ripple Stellar Monero Dash Bytecoin	5 August 2014–31 December 2018	Daily	Coinmarketcap.com	Cumulative sum (CUSUM) test for parameter stability by Page (1954) Granger causality test by Granger (1969) LM test for ARCH DCC-MGARCH model by Engle (2002)	Structural breaks are systemically present Alterations spread from small-cap cryptocurrencies to high-cap ones Volatility spillovers appear with powerful positive correlations among cryptocurrencies
Caporale and Zekokh (2019)	RIBAF	Bitcoin Ethereum Ripple Litecoin	18 July 2010–30 April 2018 (Bitcoin) 7 August 2015–30 April 2018 (Ethereum) 4 August 2013–30 April 2018 (Ripple) 28 April 2013–30 April 2018 (Litecoin)	Daily	Coindesk Price Index Coinmarketcap.com	General Markov-Switching GARCH based on Goldfeld and Quandt (1973) Following Ardia et al. (2018) SGARCH by Bollerslev (1986) EGARCH by Nelson (1991) GJR-GARCH by Glosten et al. (1993) TGARCH by Zakoian (1994) Backtesting Value-at-Risk (VaR) and Expected Shortfall (ES) Model Confidence Set (MCS) by Hansen et al. (2011) procedure for loss functions	Allowing for asymmetries and regime-switching in estimations could improve analysis by GARCH models when estimating Value-at-risk (VaR) and Expected Shortfall (ES) GARCH model is better for Bitcoin and Litecoin, GJR-GARCH and TGARCH for Ethereum and GARCH and TGARCH for Ripple (1st and 2nd regime, respectively)
Catania et al. (2018)	WP	Bitcoin Litecoin Ethereum Ripple	29 April 2013–1 December 2017 (Bitcoin, Litecoin) 8 August 2013–1 December 2017 (Ethereum) 5 August 2013–1 December 2017 (Ripple)	Daily	Coinmarketcap.com	GARCH by Bollerslev (1986) Score-Driven- GHSKT model with three extensions by Catania and Grassi (2017)	More sophisticated volatility models that include leverage and time-varying skewness lead to more accurate volatility predictions at different forecast horizons

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Chan et al. (2019)	QREF	Bitcoin SP500 Nikkei225 Shanghai A-share TSX index EUROSTOXX index	October 2010–October 2017	Daily Weekly Monthly	Coindesk Price Index (https://www.coindesk.com/price/)	GARCH(1,1) by Bollerslev (1986) Constant Conditional Correlations (CCC)-GARCH by Bollerslev (1990) DCC-GARCH by Engle (2002) Frequency dependence model by Ashley and Verbrugge (2009)	Bitcoin is effective hedge against all in monthly frequencies but not in high frequencies Bitcoin is strong hedger against SP500 and EUROSTOXX in medium frequencies and against Shanghai A-share in low frequencies
Charfeddine et al. (2019)	EM	Bitcoin Ethereum Bitcoin Cash Ripple Gold Crude Oil SP500	18 July 2010–1 October 2018 (Bitcoin) 1 September 2015–1 October 2018 (Ethereum)	Daily	Coindesk.org Coinmarketcap.com FRED database (https://fred.stlouisfed.org/.)	Different time-varying copula approaches (Gaussian, Student-t, Gumbel, Rotated-Gumbel, Joe-Clayton, SJC) BEKK-GARCH by Engle and Kroner (1995) DCC-GARCH and ADCC-GARCH based on Engle (2002) ARFIMA-FIAPARCH based on Tse (1998)	Time-varying cross-correlations of cryptocurrencies with financial assets. Cryptocurrencies are poor hedgers but good diversifiers
Charles and Darné (2019)	IE	Bitcoin	18 July 2010–1 October 2016 18 July 2010–22 March 2018	Daily	Coindesk.com	QML estimator by Bollerslev and Wooldridge (1992) Semi-parametric procedure for jump-detection by Laurent et al. (2016) GARCH by Bollerslev (1986) EGARCH by Nelson (1991) GJR-GARCH by Glosten et al. (1993) Asymmetric Power ARCH (APARCH) by Ding et al. (1993) Component GARCH (CGARCH) and Asymmetric Component GARCH (ACGARCH) by Lee and Engle (1993)	The six GARCH-type models (indicating short-memory, asymmetric effects, or long-run and short-run movement) are not appropriate for modelling Bitcoin returns

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Cheikh et al. (2020)	FRL	Bitcoin Ethereum Ripple Litecoin	28 April 2013–1 December 2018 (Bitcoin, Ripple, Litecoin) 7 August 2015–1 December 2018 (Ethereum)	Daily	Coinmarketcap.com	GARCH by Bollerslev (1986) EGARCH by Nelson (1991) GJR-GARCH by Glosten et al. (1993) Threshold GARCH (ZARCH) by Zakoian (1994) Smooth Transition GARCH (ST-GARCH) as in Luukkonen et al. (1988)	Inverted asymmetric reaction for most cryptocurrencies (good news has higher effect on volatility than bad news) Positive return–volatility relationship
Chu et al. (2017)	JRFM	Bitcoin Ripple Litecoin Monero Dash Dogecoin Maidsafecoin	22 June 2014–17 May 2017	Daily	BNC2database from Quandl	GARCH by Bollerslev (1986) EGARCH by Nelson (1991) TGARCH by Zakoian (1994) GJR-GARCH by Glosten et al. (1993) SGARCH APARCH by Ding et al. (1993) Integrated GARCH (IGARCH) by Bollerslev (1986) Component Standard GARCH (CSGARCH) by Lee and Engle (1993) Absolute Value GARCH (AVGARCH) as in Taylor (2008) NGARCH by Higgins and Bera (1992) NAGARCH by Engle and Ng (1993) ALLGARCH by Hentschel (1995)	IGARCH and GJR-GARCH are the best fit models

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Conrad et al. (2018)	JRFM	Bitcoin prices and trading volumes in USD and CNY SP500 Nikkei225 VIX index Variance Risk Premium SP Global Luxury Index (Glux) SPDR Gold Shares ETF (GLD) iPath Bloomberg Copper ETF (JJC) Baltic dry index (BDI) Google Trend data all web searches and monthly view searches)	May 2013–December 2017	Monthly Daily 5-min frequency (SP volatility)	data.bitcoinity.org Quandl The Oxford-Man Institute of Quantitative Finance Chicago Board of Options Exchange (Cboe) Google Trends	GARCH- MIxed Data Sampling (MIDAS) by Engle et al. (2013)	Negative nexus between Bitcoin volatility and US stock market volatility Bitcoin volatility is pro-cyclical (the opposite is valid for stock market volatility) so increases when global economic activity increases Bitcoin volatility reacts to higher US stock market volatility in the opposite way than gold volatility
		Bitcoin Ethereum Ripple Litecoin NEM Ethereum Classic Dash IOTA BitShares Monero Stratis EOS Zcash Steem Waves AntShares Bytecoin Golem Veritaseum Siacoin BitConnect Gnosis Iconomi Augur Stellar Lumens Lisk Dogecoin Byteball MaidSafeCoin GameCredits Factom Tether Ardor Status Decred Komodo DigiByte DigixDAO Nxt					

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Corbet et al. (2020)	JFS	Basic Attention Token PIVX FirstBlood Bancor SingularDTV MobileGo MCAP BitcoinDark SysCoin FunFair Aragon Nexus Asch Ubiq Peercoin Lykke Emercoin Ark Round LEOcoin Edgeless Storjcoin X ReddCoin Etheroll Numeraire iExec RLC Verge Melon Peerplays LBRY Credits Namecoin Wings Quantum Resistant Ledger Synereo Storj BitBay MonaCoin BlackCoin CloakCoin vSlice Elastic Counterparty Gulden OBITS Xaurum Viacoin Omni Zcoin Burst SaluS Humaniq Mysterium Vertcoin YbCoin Agoras Tokens Blocknet EarthCoin NAV Coin GridCoin TokenCard Quantum US nominal broad dollar index FOMC Policy announcemens	26 April 2013–30 June 2017	Daily	Coinmarketcap.com (own calculations for events)	GARCH by Bollerslev (1986)	Mineable digital assets are much more influenced by monetary policy volatility spillovers and feedback than non-mineable Currencies present increases, Protocols display falls whereas Decentralized Applications are not affected by global systematic liquidity spillovers

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Corbet et al. (2019a)	AEL	Bitcoin Dow Jones Industrial Average (DJIA) Kodak stock	22 November 2017–21 February 2018	5-min frequency	Cryptocompare.com Bloomberg	GARCH by Bollerslev (1986) DCC-GARCH by Engle (2002)	Higher share price and volatility for Kodak after the announcement about Kodakcoin launch Higher correlation between Kodak stock and Bitcoin New form of asymmetric information
Corbet et al. (2017)	IMFI	Bitcoin SP500 EUSROSTOXX 50 Trade-weighted index of domestic currency against USD, EUR, JPY and GBP Gold WTI Crude oil	19 July 2010–29 April 2016	Daily	Coindesk.com Bloomberg	OLS GARCH by Bollerslev (1986)	Decisions about QE announced by the Federal Reserve, the Central Bank of England, the European Central Bank and the Bank of Japan increase volatility in Bitcoin returns
Dyhrberg (2016a)	FRL	Bitcoin Gold bullion USD/troy ounce rate CMX Gold futures 100 ounce rate USD/EUR and USD/GBP exchange rates Financial Times Stock Exchange (FTSE) index Federal Funds Rate (FFR)	19 July 2010–22 May 2015	Daily	Coindesk Price Index Datastream Federal Reserve bank of New York	GARCH by Bollerslev (1986) EGARCH by Nelson (1991)	Bitcoin is similar to gold and US dollar Bitcoin reacts to changes in FFR and to good and bad news and is a hedger
Dyhrberg (2016b)	FRL	Bitcoin Price Index USD/EUR and USD/GBP exchange rates FTSE index	19 July 2010–22 May 2015	Daily	Datastream Coindesk Bitcoin Price Index (www.coindesk.com)	Asymmetric GARCH as in Capie et al. (2005) Threshold-GARCH (TGARCH(1,1))	Bitcoin can act as a hedger against the FTS index. Moreover, it can be a hedger against the US dollar only in the short-run.

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Fakhfekh and Jeribi (2019)	RIBAF	Bitcoin Augur OES Ethereum BitShares Dash IOTA Komodo LISK Monero Ripple Stellar NEO QTUM Stratis Waves	7 August 2017–12 December 2018	Daily	Coinmarketcap.com ABC bourse	GARCH by Bollerslev (1986) EGARCH by Nelson (1991) TGARCH by Zakoian (1994) Power GARCH (PGARCH) by Ding et al. (1993) Fractionally Integrated GARCH (FIGARCH) by Baillie et al. (1996) Fractionally Integrated Exponential GARCH (FIEGARCH) by Bollerslev and Mikkelsen (1996)	TGARCH with double exponential distribution is the most appropriate for Augur, BitShares, Monero, NEO, Ripple and Waves. TGARCH is most suitable for Komodo and Stratis, EGARCH with double exponential distribution for IOTA whereas under student-t distribution for QTUM
Glaser et al. (2014)	SSRN	Bitcoin	1 January 2011–8 October 2013	Daily	Mt. Gox Bitcoin charts Bitcoin Blockchain	GARCH by Bollerslev (1986)	Initial attention on Bitcoin and its usage in transaction increase its demand. Mainly speculative motives of investors
Gronwald (2014)	CES	Bitcoin	7 February 2011–24 February 2014	Daily	Mt. Gox	Jump-intensity GARCH based on Chan and Maheu (2002) GARCH by Bollerslev (1986)	Bitcoin is characterized by extreme price movement and its market is not mature The jump-intensity GARCH is more suitable for estimations

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Guesmi et al. (2019)	IRFA	Bitcoin (from Bitstamp) MSCI Emerging Markets Index MSCI Global Market Index Euro and Chinese exchange rates Gold (gold bullion) West Texas Intermediate (WTI) Oil Implied Volatility Index (VIX)	1 January 2012–5 January 2018	Daily	Datastream Eurostat Federal Reserve Bank of St. Louis	VARMA(1,1)-BEKKAGARCH VARMA(1,1)-DCC-GARCH VARMA(1,1)-DCC-EGARCH VARMA(1,1)-DCCGJR-GARCH by Glosten et al. (1993) VARMA(1,1)-DCC-FIAPARCH by Aielli (2008) and Engle (2002) VARMA(1,1)-cDCC-GARCH VARMA(1,1)-cDCC-EGARCH VARMA(1,1)-cDCC-FIGARCH ARMA(1,1)-cDCC-GJR-GARCH VARMA(1,1)-ADCC-GARCH VARMA(1,1)-ADCC-EGARCH VARMA(1,1)-ADCCFIGARCH VARMA(1,1)-cADCC-GARCH VARMA(1,1)-cADCC-EGARCH VARMA(1,1)-cADCC-GJR-GARCH VARMA(1,1)-cADCC-FIGARCH	VARMA(1,1)-DCC-GJR-GARCH is the most suitable model for describing the joint dynamics of Bitcoin and other assets Significant return and volatility spillovers. Bitcoin could make a good hedger
Jin et al. (2019)	Phys	Bitcoin Gold (Gold fixing Price 10:30 a.m. in London Bullion Market) WTI Crude Oil	10 May 2013–7 September 2018	Weekly	Coinmarketcap.com Federal Reserve Bank of St. Louis Energy Information Administration (EIA)	Multifractal Detrended cross-correlation analysis (MF-DCCA) Multivariate GARCH (MVGARCH) by Engle (2002) Information Share (IF) analysis by Hasbrouck (1995, 2002)	Multifractality exists across correlation between Bitcoin, gold and crude oil. Bitcoin is more susceptible to price fluctuations from gold and crude oil. Bitcoin market absorbs information less easily compared to gold.

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Kang et al. (2019)	Phys	Bitcoin Gold futures	26 July 2010–25 October 2017	Weekly	Coindesk price index (www.coindesk.com) Thomson Reuters database	DCC-GARCH by Engle (2002) Wavelet coherence analysis as in Torrence and Webster (1999)	Volatility persistence, causality and phase differences between Bitcoin and gold futures Contagion is higher during the European sovereign debt crisis Wavelet coherence estimations indicate high levels of co-movement across the 8-16 weeks frequency band
Katsiampa (2017)	EL	Bitcoin	18 July 2010–1 October 2016	Daily	Coindesk price index (www.coindesk.com)	GARCH by Bollerslev (1986) EGARCH by Nelson (1991) TGARCH by Zakoian (1994) Asymmetric Power ARCH (APARCH) by Ding et al. (1993) Component GARCH (CGARCH) by Lee and Engle (1993) Asymmetric Component GARCH (ACGARCH)	AR-CGARCH is the most suitable model for Bitcoin estimation
Katsiampa (2019a)	FRL	Bitcoin Ethereum	7 August 2015–15 January 2018	Daily	Coinmarketcap.com	Diagonal BEKK based on Engle and Kroner (1995)	Interdependencies exist in the cryptocurrency market Ethereum could effectively hedge against Bitcoin Optimal portfolio weights analysis reveals that Bitcoin should outweigh Ethereum

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Katsiampa (2019b)	RIBAF	Bitcoin Ethereum Ripple Litecoin Stellar Lumen	7 August 2015–10 February 2018	Daily	Coinmarketcap.com	Asymmetric Diagonal BEEK by Kroner and Ng (1998)	The conditional covariance of all cryptocurrencies examined are affected by both past squared errors and past conditional volatility Asymmetric past shocks in Bitcoin, Ethereum, Ripple and Litecoin significantly affect the current conditional covariance The time-varying conditional correlations are mostly positive Volatility is responsive to major news
Katsiampa et al. (2019a)	JIFMIM	Bitcoin Ethereum Litecoin Dash Ethereum Classic Monero Neo OmiseGO	15 eptember 2017 (11:00 p.m.)–1 July 2018 (12:00 a.m.)	Hourly	Bitrex	Diagonal BEKK based on Engle and Kroner (1995) Asymmetric Diagonal BEKK by Kroner and Ng (1998)	Conditional variances strongly affected by previous squared errors and past conditional volatility Strong and positive correlations Investors pay more attention to news about Neo and the least to news about Dash Shocks in Bitcoin persist the most while in OmiseGo the least

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Katsiampa et al. (2019b)	FRL	Bitcoin Ethereum Litecoin	7 August 2015–10 July 2018	Daily	Coinmarketcap.com	Three pairwise bivariate BEKK models based on Engle and Kroner (1995)	Price volatility of digital currencies depends on its own past shocks and past volatility. Bi-directional shock transmission impacts between Bitcoin and both Ethereum and Litecoin, Uni-directional shock spillovers from Ethereum to Litecoin Bi-directional volatility spillover effects between all the three pairs Mostly positive time-varying conditional correlations
King and Koutmos (2021)	AOR	Bitcoin Ethereum Ripple Bitcoin Cash EOS Litecoin Stellar Cardano IOTA	Each Initial Coin Offering–6 August 2020	Daily	Coinmarketcap.com	EGARCH based on Nelson (1991) Modified Value-at-Risk Modified Sharpe Ratio	Heterogeneity in the types of ffedback trading strategies. Some cryptocurrency markets show evidence of ''herding" or ''trend chasing" behaviours while in other markets contrarian-type behaviour is detected.
Klein et al. (2018)	IRFA	Bitcoin Market-weighted cryptocurrency index (CRIX) by Trimborn and Härdle (2018) Gold (in USD per oz) Silver (in USD per oz) WTI crude oil SP500 index MSCI World MSCI Emerging Markets 50	1 July 2011–31 December 2017 31 July 2014–31 December 2017 (CRIX)	Daily	Datastream (with GMT Timestamp) Coindesk.com (with GMT Timestamp) Crix.hu-berlin.de website	BEKK-GARCH based on Engle and Kroner (1995)	Bitcoin completely different behavior from gold, particularly in market distress Bitcoin is not a stable hedger against equity investments

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Koutmos (2019)	AOR	Bitcoin US total market price index CBOE volatility index Default spread Relative 3-month treasury bill rate Term spread Inflation expactations Deutsche bank FX volatility index	2 January 2013–20 September 2017	Daily	Bloomberg Prof. French's website	Markov Regime-switching Model	Heterogeneity in the explanatory power of market risk factors between periods of low and high Bitcoin volatility. High volatility renders the explanation of Bitcoin returns more difficult.
Koutmos and Payne (2021)	RQFA	Bitcoin	28 April 2013–1 March 2020	Daily	-	EGARCH based on Nelson (1991) Markov Regime-switching Model Modified Value-at-Risk Modified Sharpe Ratio	Mean-variance optimizers speculators that engage in ''bandwagon behaviour", and fundamentalists that trade when fundamental values deviate from long-run values exist. Fundamentalists exhibit contrarian-type behavious in low-volatility regimes.
Kristoufek (2021)	FRL	Bitcoin Ethereum Ripple Tether Omni Ethereum TRX Binance USD HUSD Paxos Standard USD Coin Dai Gemini Dollar Single Collateral DAI TrueUSD USDK	1 January 2016–12 January 2021	Daily	Coinmetrics.io	Generalized Vector Autoregressive (VAR) framework based on (Koop et al. 1996) and Pesaran and Yongcheol (1998)	Stablecoins do not have positive impacts on prices of other cryptocurrencies

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Kumar and Anandarao (2019)	Phys	Bitcoin Ethereum Ripple Litecoin	15 August 2015–18 January 2018	Daily	Coinmarketcap.com	IGARCH(1,1)-DCC GARCH(1,1) by Engle (2002) and Bollerslev (1986) Wavelet coherence analysis Cross-spectra	Significant volatility spillover from Bitcoin to Ethereum and Litecoin Increased volatility spillovers of cryptocurrencies after 2017 Wavelet coherence analysis reveals persistent correlations in the short-run Herding behaviour in cryptocurrency markets
Kyriazis et al. (2019)	Hel	Bitcoin Ethereum Ripple Dogecoin Zcash OmiseGo Bitcoin Gold Bytecoin Lisk Tezos Monero Decred Nano BitShares	1 January 2018–16 September 2018	Daily	Coinmarketcap.com	ARCH by Engle (1982) GARCH by Bollerslev (1986) EARCH by Nelson (1991) EGARCH Threshold ARCH (T-ARCH) Threshold SDGARCH (T-SDGARCH) based on Zakoian (1994) GJR-Threshold ARCH (GJR T-ARCH) based on Glosten et al. (1993) GJR-Threshold GARCH (GJR T-GARCH) Simple asymmetric ARCH (SA-ARCH) Simple asymmetric GARCH (SA-GARCH) as in Pagan and Schwert (1990) Power ARCH (P-ARCH) by Ding et al. (1993) Power GARCH (P-GARCH) Nonlinear ARCH (N-ARCH) Nonlinear GARCH (N-GARCH) Nonlinear ARCH (N-ARCH) with one shift based on Higgins and Bera (1992)	Complementarity between cryptocurrencies and no hedging abilities in the majority of them DOGE and BTG are better estimated by Power ARCH, ZEC and BNB by GJR-TGARCH, BTS by T-SDGARCH, OMG by SA-GARCH. Additionally, XTZ is explained better by AP-GARCH, XEM by P-GARCH, DCR by NP-GARCH, LSK by EGARCH, BCN and NANO by EARCH

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
						Nonlinear GARCH (N-GARCH)with one Shift Asymmetric Power ARCH (AP-ARCH) by Ding et al. (1993) Asymmetric Power GARCH (AP-GARCH) Nonlinear Power ARCH (NP-ARCH) based on Higgins and Bera (1992) Nonlinear Power GARCH (NP-GARCH)	
Mensi et al. (2019)	FRL	Bitcoin Ethereum	1 July 2011–3 March 2018 (Bitcoin) 9 August 2015–3 March 2018 (Ethereum)	Daily	Coindesk Price Index Coinmarketcap.com	GARCH Fractionally Integrated (FI)-GARCH by Baillie et al. (1996) Fractionally Integrated Asymmetric Power GARCH (FIAPARCH) by Tse (1998) Hyperbolic GARCH (HYGARCH) by Davidson (2004)	Dual long memory and structural changes in Bitcoin and Ethereum, no market efficiency Persistence levels in returns and volatility fall after accounting foe long memory and structural changes FIGARCH provides better accuracy in predictions

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Narayan et al. (2019)	EMR	Bitcoin Inflation rate Import Price Index Unemployment rate for Indonesia Crude Oil Prices (West Texas) Output gap IND (Indonesian Rupee)/USD exchange rate Difference between United States and Indonesian 1-month Interbank Rate Difference of the logarithm of industrial production (IP) of the US and Indonesia Velocity of M1 and M2 Real GDP 1-month and 3-month Interbank rate	September 2011–April 2018	Monthly	Coinmarketcap.com International Financial Statistics (IFS) Bank Indonesia Global Financial Database Bloomberg Author's own calculations	GARCH and ARMA-GARCH based on Bollerslev (1986)	Bitcoin's price growth leads to inflation growth, currency appreciation and lower money velocity in Indonesia
Omane-Adjepong and Alagidede (2019)	RIBAF	Bitcoin BitShares Litecoin Stellar Ripple Monero Dash	8 May 2014–12 February 2018	Daily	Coinmarketcap.com	Multiscale wavelet method as in Fernández-Macho (2012) Granger causality in VAR by Granger (1969) GARCH GJR-GARCH by Glosten et al. (1993)	Bitcoin and Ripple are the most influential concerning spillovers Lower to moderate correlations exist in the multiple movements in markets, especially within intraweek to monthly scales Connectedness and volatility causality is sensitive to trading scales and the proxy for market volatility

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Omane-Adjepong et al. (2019)	Phys	Bitcoin Ethereum Ripple Litecoin Stellar Monero Dash NEM	25 August 2015–13 March 2018	Daily	Coinmarketcap.com	ARFIMA-FIGARCH by Baillie et al. (1996) under Caussian and Student-t distribution with a modified log-periodogram	Information efficiency and volatility persistence are revealed that are sensitive to time scales, the measure of returns and volatilities and regime shift.
Peng et al. (2018)	Exp	Bitcoin Ethereum Dash EUR/USD, GBP/USD, JPY/USD exchange rates	4 January 2016–31 July 2017	Hourly Daily	Altcoin Charts (http://alt19.com) Forex Historical Data (http://fxhistoricaldata.com)	GARCH by Bollerslev (1986) EGARCH by Nelson (1991) GJR-GARCH Support by Glosten et al. (1993) Support Vector Regression (SVR) as in Drucker et al. (1997)–GARCH Diebold and Mariano (2002) test and Hansen's Model Confidence Set by Hansen et al. (2011) for evaluation of model's predictive ability	SVR- GARCH specifications outperform all nine GARCH bench- marks –GARCHs, EGARCHs and GJR-GARCHs with Normal, Student's t and Skewed Student's t distributions
Sensoy (2019)	FRL	Exchange rates of BTC/USD and BTC/EUR	1 January 2013–5 March 2018	Intraday (15-, 20-, 30-, 40-, 45 min)	1coin, abucoins, allcoin, aqoin, anxhk, bitbay, bitkonan, bitstamp, btcalpha, btcc, b2c, b7, bcmBM, bcmLR, bcmMB, bcmPP, bitalo, bitbox, bitcurex, bitfinex, bitfloor, bitmarket, bitme, btc24, btce, btcex, btcexWMZ, btctree, bc, btcde, btceur, coinfalcon, cex, coinbase, coinsbank, cbx, cotr, cryptox, crytr, exchb, exmo, fbtc, global, hitbtc, itbit,	Permutation entropy by Bandt and Pompe (2002) GARCH(1,1)	BTC/USD and BTC/EUR have become informationally more efficient intradaily since early 2016 BTC/USD market is slightly more efficient than the BTC/EUR market Higher frequency data reveal more opportunities for profit Positive nexus of liquidity with efficiency, negative linkage of volatility with efficiency

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
					ibwt, imcex, indacoin, intrsng, just, kraken, lake, localbtc, lybit, mtgox, okcoin, ripple, rock, ruxum, thLR, th, vcx, weex, and zyado exchanges		
Symitsi and Chalvatzis (2018)	EL	Bitcoin S&P Global Clean Energy Index MSCI World Energy Index MSCI World Information Technology Index	22 August 2011–15 February 2018 22 August 2011–31 December 2017 (replication)	Daily	Datastream	VAR(1)-BEKK-AGARCH by McAleer et al. (2009)	Significant return spillovers from energy and technology stocks to Bitcoin Long-run volatility impacts from Bitcoin on fossil fuel and clean energy stocks are traced Bilateral negative shock spillovers between Bitcoin and stock indices Bitcoin presents low correlation with stock indices so diversification is possible
Tiwari et al. (2019)	Phys	Bitcoin Ethereum Ripple Litecoin Dash Stellar SP500 index	7 August 2015–15 June 2018	Daily	Coindesk Price Index Thomson Reuters Datastream	ARMA-EGARCH by Nelson (1991) Copula-DCC-EGARCH Copula-ADCC-EGARCH based on Engle (2002) and Nelson (1991)	Cryptocurrencies (especially Ethereum) are hedgers against the SP500 index Volatilities respond more to negative shocks in comparison to positive one sin both markets

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Troster et al. (2019)	FRL	Bitcoin	19 July 2010–16 April 2018	Daily	Coindesk.com	GARCH by Bollerslev (1986) EGARCH by Nelson (1991) APARCH by Ding et al. (1993) TGARCH by Zakoian (1994) GJR-GARCH by Glosten et al. (1993) CGARCH NGARCH HGARCH by Hentschel (1995) (all GARCH specifications are tested with innovation distributed as: Normal (N), t-Student (tS), Skewed t-Student (StS), Johnson's Reparametrized SU (JSU), and Generalized Error Distribution (GED)) Generalized Autoregressive Score (GAS) models by Creal et al. (2013) and Harvey (2013) GAS-N GAS-tS GAS-StS GAS-AST GAS-AST1	Heavy-tailed GARCH or GAS models outperform normally distributed GARCH models Heavy-tailed GAS models provide the best conditional and unconditional coverage for 1% VaR forecasts
Tu and Xue (2018)	FRL	Bitcoin Litecoin	28 April 2013–31 July 2017 1 August 2017–31 July 2018	Daily	Coinmarketcap.com	Granger causality test by Granger (1969) BEKK-MGARCH by Engle and Kroner (1995)	Retur and volatility spillovers from Bitcoin to Litecoin before the bifurcation, while the other way around after the bifurcation Overall, the bifurcation has weakened Bitcoin's dominant place in the cryptocurrency market

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Urquhart and Zhang (2019)	IRFA	Bitcoin AUD CAD CHF EUR JPY GBP	1 November 2014–31 October 2017	Hourly	www.bitcoincharts.com (Bitstamp exchange)	DCC-GARCH based on Bollerslev (1986) DCC-EGARCH based on Nelson (1991) DCC-GJR-GARCH based on Glosten et al. (1993) ADCC-GARCH by Cappiello et al. (2006) ADCC-EGARCH ADCC-GJR-GARCH Non-temporal Hansen (2000) test for detecting safe haven properties	Bitcoin can act as an intraday hedger against CHF, EUR and GBP while as a diversifier for AUD, CAD and JPY Bitcoin constitutes a safe haven for CAD, CHF and GBP during extreme market turmoil
Vidal-Tomás and Ibañez (2018)	FRL	Bitcoin Events in Bitcoin markets Monetary policy events related to the Federal Reserve, the European Central Bank, Bank of Japan and Bank of England	13 September 2011–17 December 2017 (Bitstamp) 13 September 2011 to 25 February 2014 (Mt. Gox)	Daily	BCHARTS/BITSTAMPUSD (Bitstamp) BCHARTS/MTGOXCAD (Mt.Gox) Feng et al. (2018) and Coindesk.com (events)	Event study analysis AR-CGARCH-M as in Katsiampa (2017)	Bitcoin is semi-strong inefficient in response to monetary policy news but is responsive and more efficient regarding negative news in the Bitstamp and Mt. Gox markets
Yu et al. (2019)	IPM	Bitcoin prices and trading volume	1 January 2015–31 October 2017	Daily	Blockchain.info	GARCH by Bollerslev (1986) EGARCH by Nelson (1991) GJR-GARCH by Glosten et al. (1993)	Persistence in Bitcoin volatility is high Bitcoin market presents greater efficiency than financial markets overall and supports the sequential information arrival hypothesis The growth rate of Google trends exhibits statistically significant impacts on volatility in Bitcoin returns

Table A1. *Cont.*

Authors	Journal	Variables	Period Examined	Data Frequency	Source	Methodology	Findings
Yu (2019)	Phys	Bitcoin (open, high, low, close, volume and weighted price of all active Bitcoin markets) Economic Policy Uncertainty index	1 March 2003–31 September 2018	5-min frequency	Bitcoincharts.com www.policyuncertainty.com	Heterogeneous Autoregressive (HAR) model by Corsi (2009) based on Müller et al. (1997) HAR-Realized Volatility (HAR-RV) by Andersen and Bollerslev (1998) HAR with Continuous volatility and Jumps (HAR-CJ) by Andersen et al. (2007) Leverage HAR (LHAR)-CJ of Corsi and Renò (2012) HAR-CJ-Economic Policy Uncertainty (EPU) LHAR-CJ-EPU Model Confidence Set (MCS) test by Hansen et al. (2011)	The leverage effects can influence future volatility significantly and are more powerful than jump component in forecasting Bitcoin volatility Adding the leverage effect and Economic Policy Uncertainty to the benchmark model can significantly improve predictive ability

Abbreviations for journals are as follows: **AEL:** Applied Economics Letters, **AOR:** Annals of Operational Research, **CES:** Center of European Studies Working Paper, **EB:** Economics Bulletin, **EL**: Economics Letters, **EM**: Economic Modelling, **EMR**: Emerging Markets Review, **EXP**: Expert Systems with Applications, **FRL**: Finance Research Letters, **HEL**: Heliyon, **IE**: International Economics, **IMFI**: Investment Management and Financial Innovations **IPM**: Information Processing and Management, **IRFA**: International Review of Financial Analysis, JFS: Journal of Financial Stability, **JIFMIM**: Journal of International Financial Markets, Institutions and Money, **MPRA**: Munich Personal Repec Archive **PHYS**: Physica A: Statistical Mechanics and its Applications, **SSRN**: Working Paper in SSRN, **QREF**: The Quarterly Review of Economics and Finance, **RI**: Research in Economics, **RIBAF**: Research in International Business and Finance, and **RQFA**: Review of Quantitative Finance and Accounting.

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